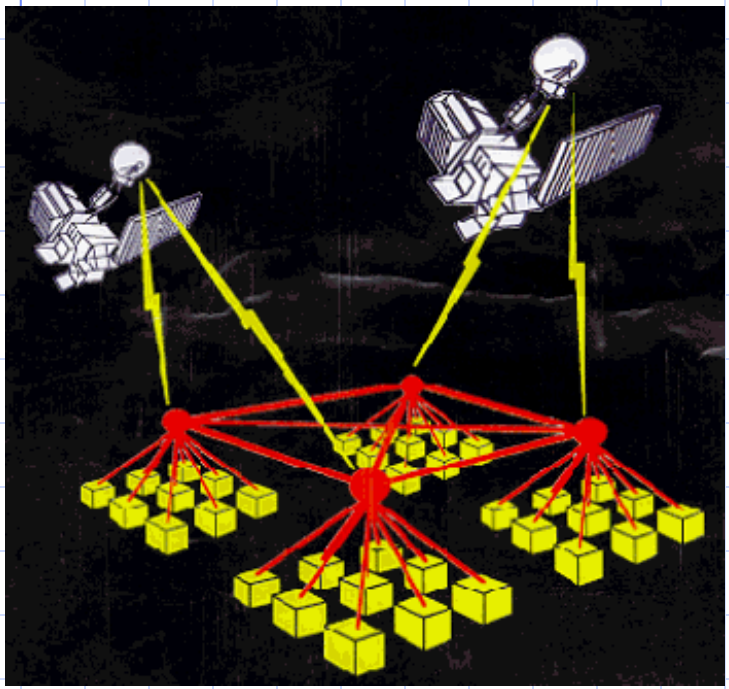
MU-FASHION

Multi-Resolution Data Fusion using Agent-Bearing Sensors In Hierarchically-Organized Networks



Project Participants:

- Krishnendu Chakrabarty (Duke University)
- S. S. Iyengar (Louisiana State University
- Hairong Qi (University of Tennessee)

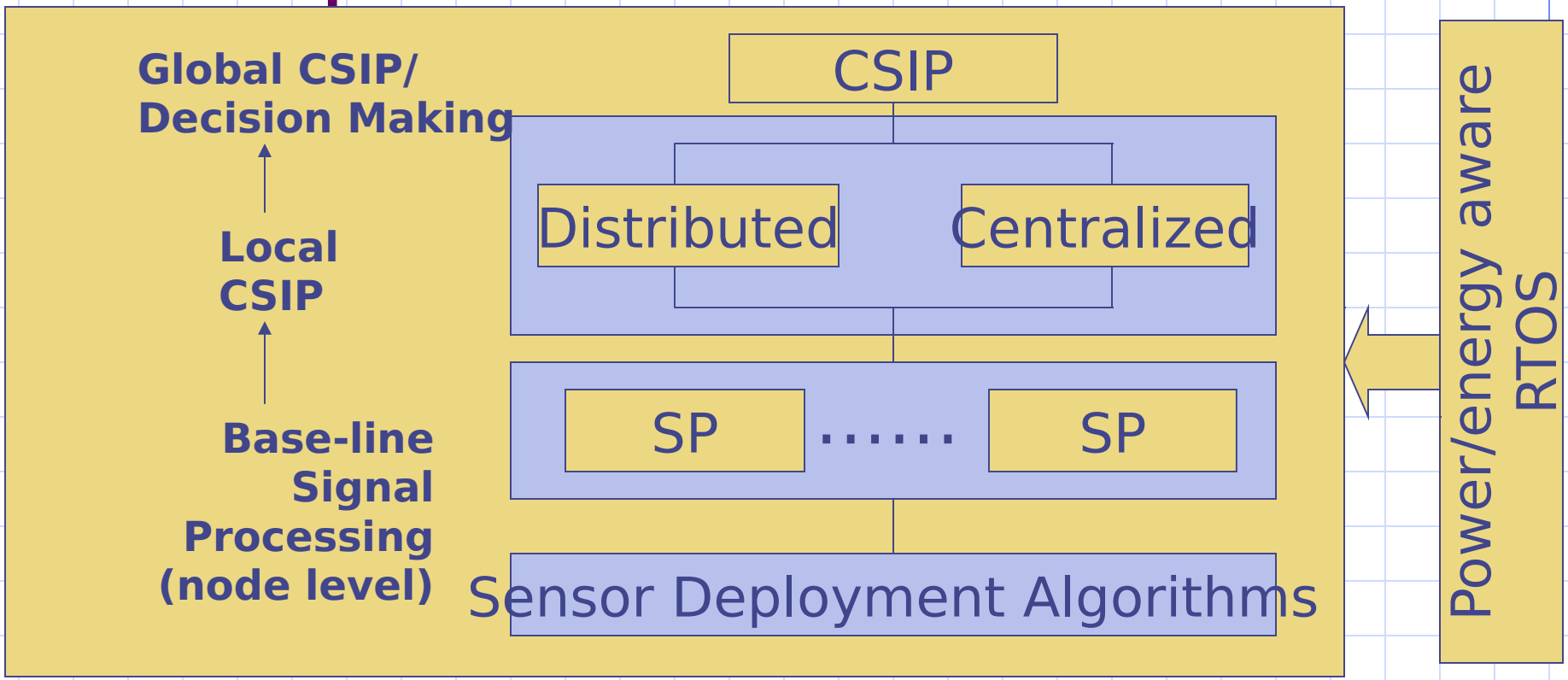
DARPA SensIT PI Meeting
Jan 17, 2002

//www.ee.duke.edu/~vishnus/DARPA/darpa.htm

Other Project Participants

- Vishnu Swaminathan (Duke University)
- Charles Schweizer (Duke University)
- Xiaoling Wang (University of Tennessee)
- Yuxin Tian (University of Tennessee, graduated)
- Yingyue Xu (University of Tennessee)
- Phani Teja Kuruganti (University of Tennessee)
- Qishi Wu (Louisiana State University)
- Lei Xu (Louisiana State University)

Project Goals and Components



- Collaborative signal processing: energy aware, fault-tolerant, progressive accuracy
- Power management in real-time OS
- Fundamental research on sensor deployment

Accomplishments & National Recognition

- Fundamentals and new ideas
- Publications
- Experimentation and integration activities
- ONR Young Investigator Award (Chakrabarty)
- ACM Fellow (Iyengar)

Accomplishments (Fundamentals & New Ideas)

- Collaborative signal processing based on mobile agent paradigm
- Low-energy task scheduling for real-time operating systems (RTOS)
- Energy-driven I/O device scheduling algorithms
  - Pruning-based optimal algorithm
- Analytical battery modeling
  - Experimental validation of discharge and recovery
- Robust sensor deployment algorithms
  - NP-Completeness proofs for sensor coverage problems
  - Sensor deployment for a planar grid formulated as multidimensional combinatorial optimization problem. Maximize overall detection probability for given cost.

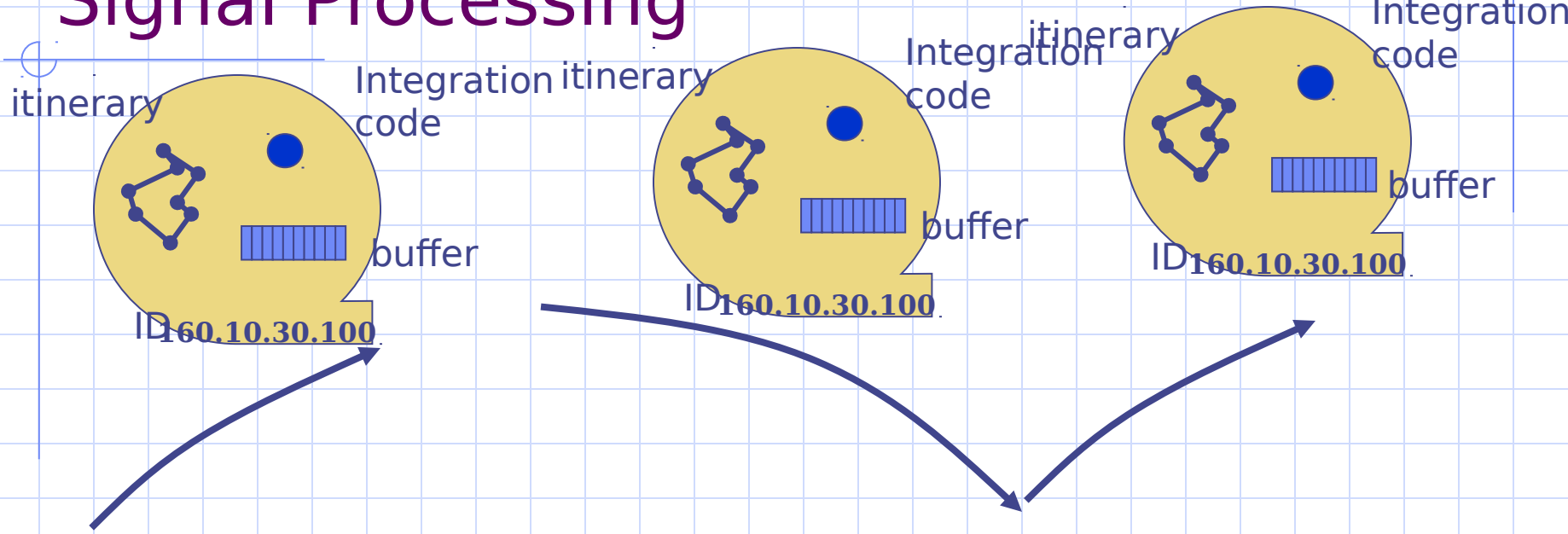
Accomplishments (Publications since April 2001)

- Conference papers: 4 published, 2 accepted, 1 submitted (under review)
- Journal papers: 3 published, 2 accepted, 2 submitted
- Guest editing of special issue of *Journal of the Franklin Institute*
- Guest editing of special issue of *International Journal of High Performance Computing Applications – Special issue on Sensor Networks*

Accomplishments (Integration and Experimentation Activities)

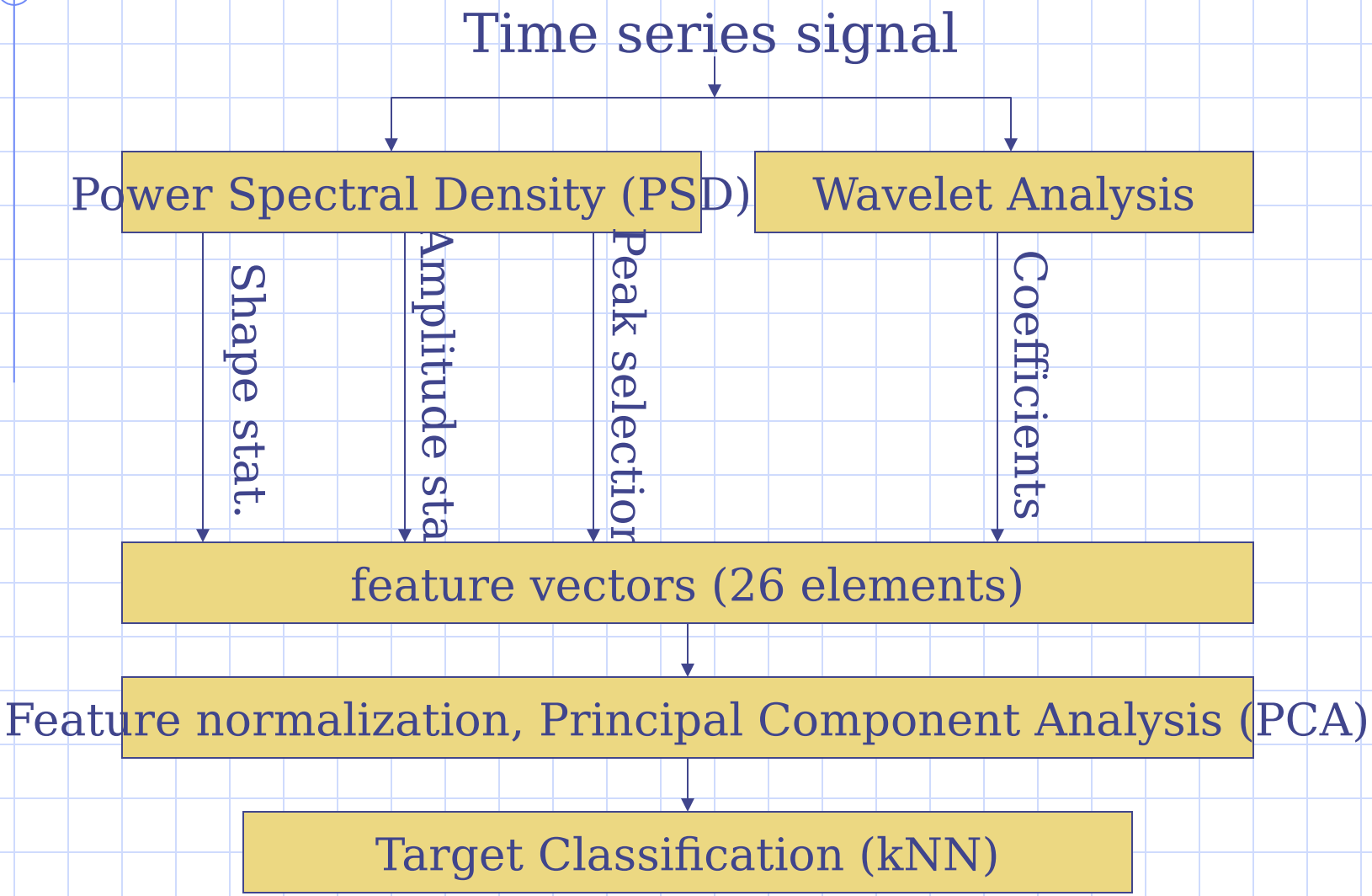
- Successfully deployed mobile agent for collaborative target classification
- Successful integration with BAE's low-level signal processing and Auburn's distributed service for target classification and localization
- Could not integrate with PSU/ARL mobile code due to problems during compilation
- Attempted to port RTOS prototype to WINS 2.0 node
  - Effort unsuccessful due to hardware difficulties, lack of technical support
- Successful in setting up a test bed based on the AMD Athlon-4 processor

Mobile-Agent-based Collaborative Signal Processing

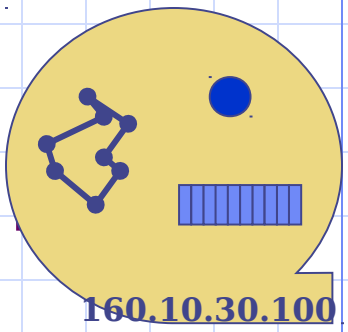


- Power-aware
- Progressive accuracy
- Small amount of data transfer
- Task adaptive

Local Target Classification



Classification and Fusio



- Classification method: k-Nearest-Neighbors (kNN)
- Procedures of data fusion (At each node i, use kNN for each k∈{5,...,15})

	Class 1	Class 2	...	Class n
k=5	3/5	2/5	...	0
k=6	2/6	3/6	...	1/6
...	...	...	...	...
k=15	10/15	4/15	...	1/15

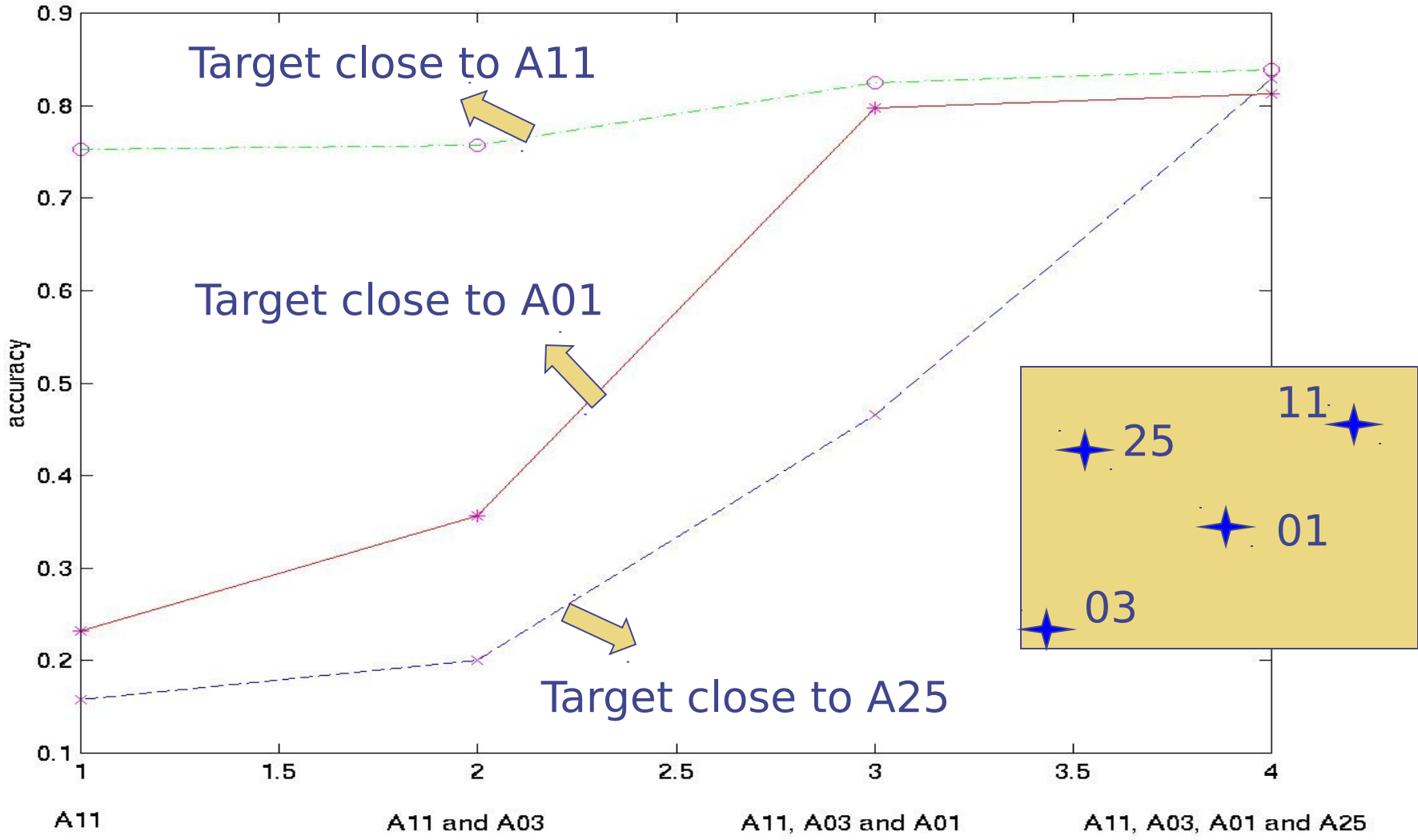
confidence level

{2/6, 10/15} **{4/15, 3/6}** ... **{0, 1/6}** ← confidence range

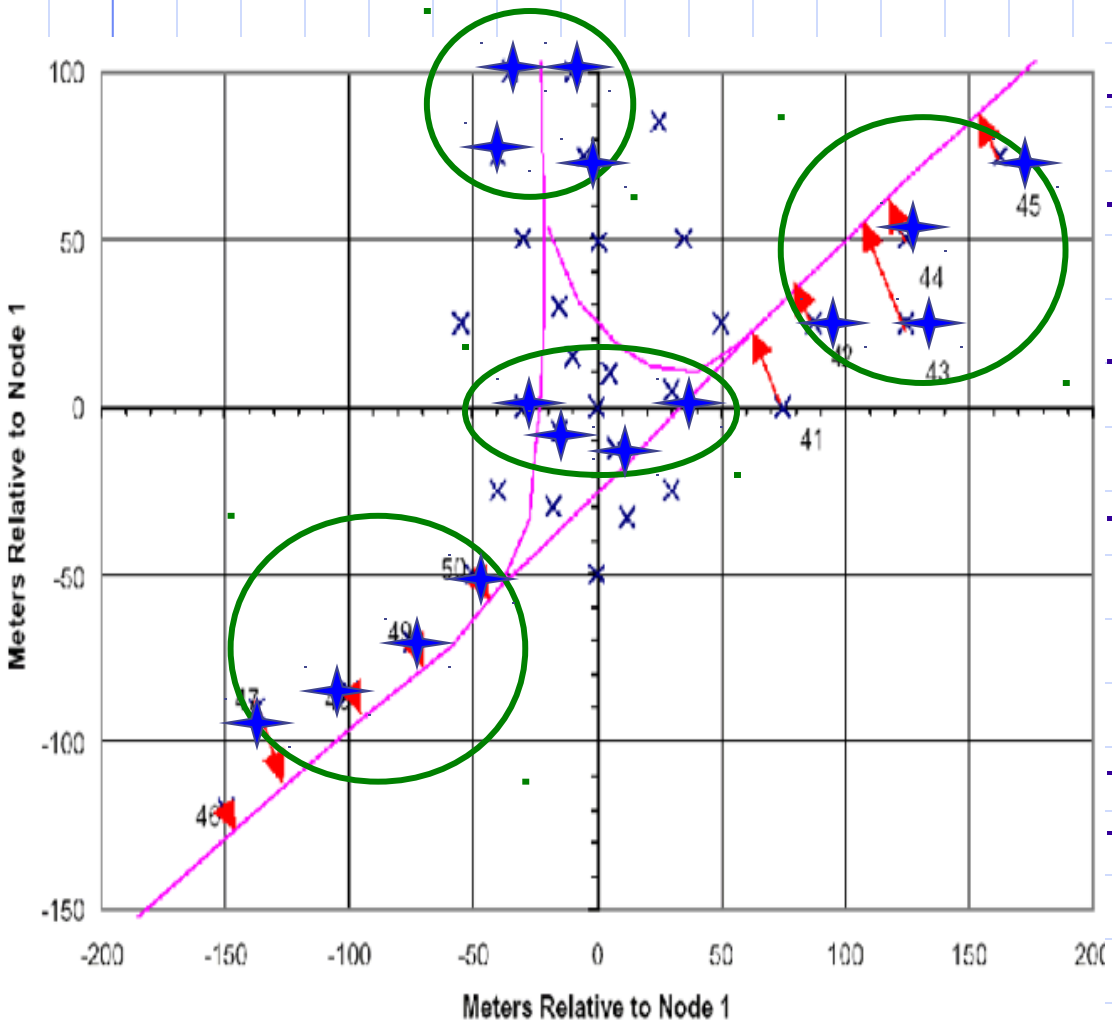
smallest largest in this column

- Use the confidence ranges generated from each node as the overlapping function, apply multi-resolution integration (MRI) algorithm to get the fusion result

Performance Gain Using Fusion



November 2001 Demo Results



- Participate in the developmental demo
- Mobile-agent-based target classification is tested over Ethernet
- Mobile agents are deployed in four clusters with each cluster having four nodes
- Our training set has seismic data for AAV, DW, LAV, POV. During our time frame, available targets include AAV, LAV, DW, HMMVV
- Misclassify HMMVV as POV
- Correctly classify DW and AAV, LAV

Target Localization

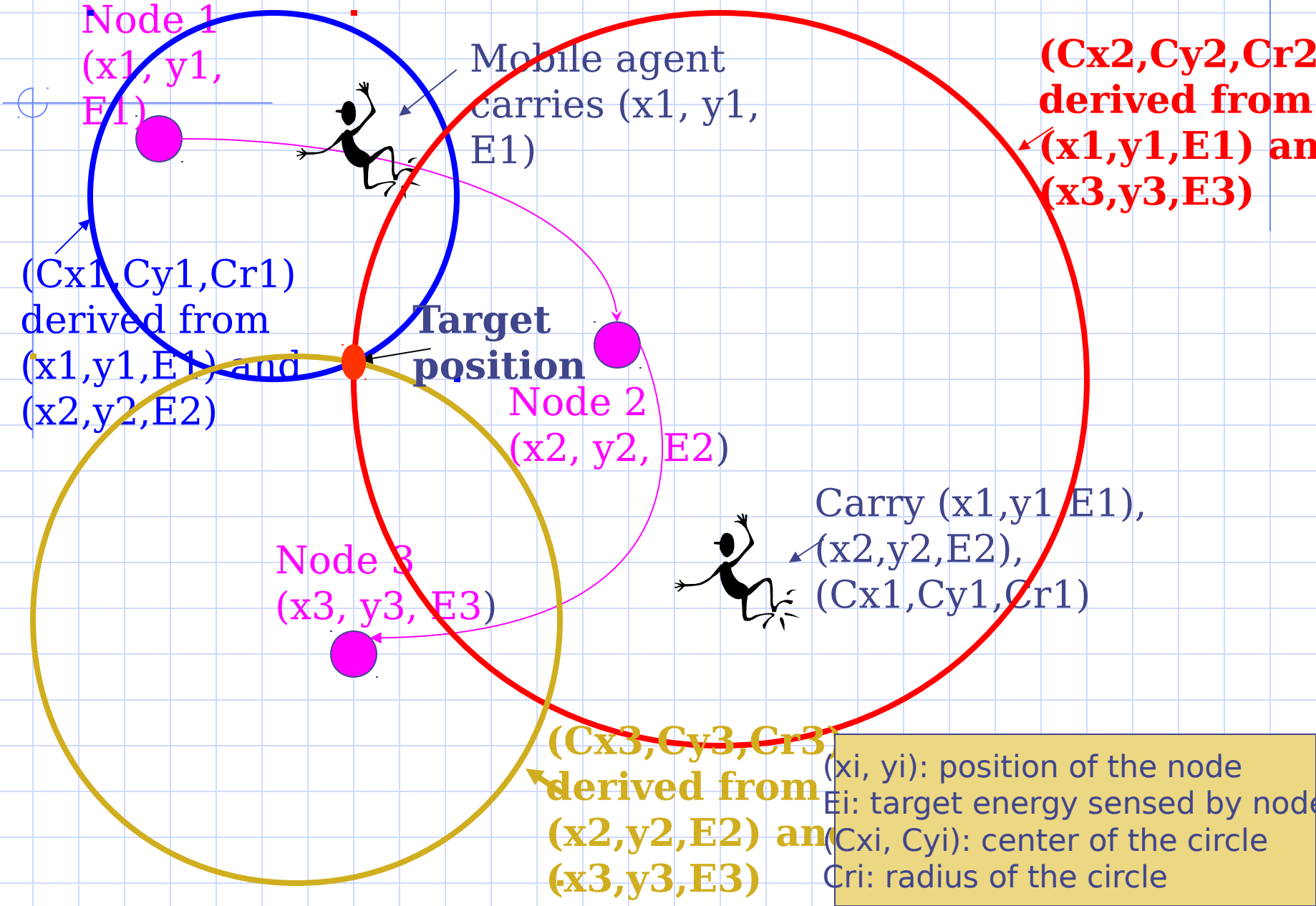
- Use the energy measurements at each node and the energy decay model of signals to derive a circle indicating the possible position of a target

$$\frac{|r(t) - r_i|}{|r(t) - r_j|} = \left(\frac{E_i(t)}{E_j(t)} \right)^2$$

r_i is the position of node i

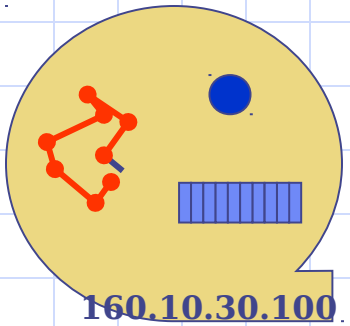
$E_i(t)$ is the target energy sensed by node i at time t

Illustration of Localization



Mobile-Agent-based Collaborative Signal Processing – Location Centric Itinerary

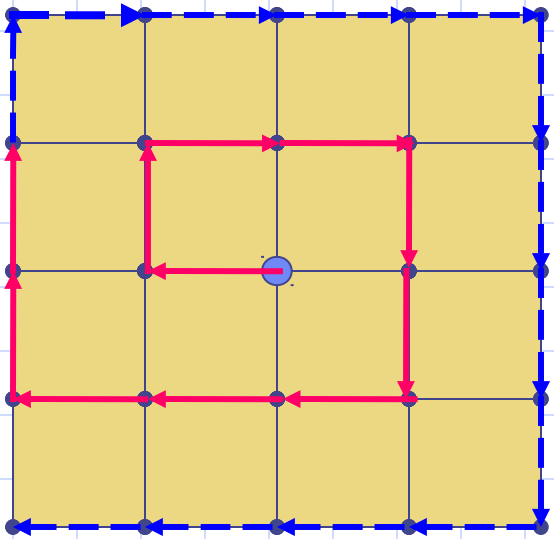
- Goals
  - Computationally efficient and Power efficient
  - Adaptability
  - Progressive accuracy
  - Real-time response

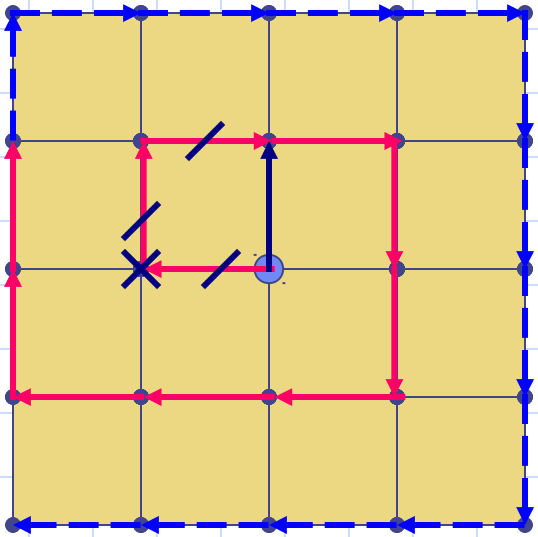


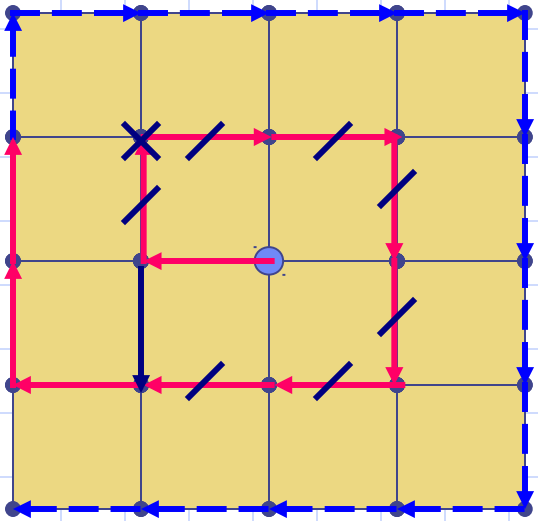
- Location-centric
  - Each mobile agent is in charge of fusing data from sensors located in a certain area
- New features (Itinerary vs. Routing)
  - Each node provides the same information with different accuracy
  - Destination is unknown - every node is a potential destination

Ad Hoc Dynamic Itinerary Planning

- Local closest first (LCF)
  - Faster in approaching the accuracy requirement
  - Dash-line indicates the idea that the mobile agent does not have to migrate through all of the sensors in the cluster if it has achieved the accuracy requirement
- Spiral itinerary







Optimal Itinerary Design

- Other factors need to be considered
  - **Sensing quality (0 <= Hq <= 1)**
  - **Hops needed from the current node (i)**
  - **Leverage our dynamic power management research to handle constraint of remaining sensor power (0 <= Hp <= 1)**
- Objective function

$$H = \alpha H_q + \beta H_p \qquad \alpha + \beta = 1$$

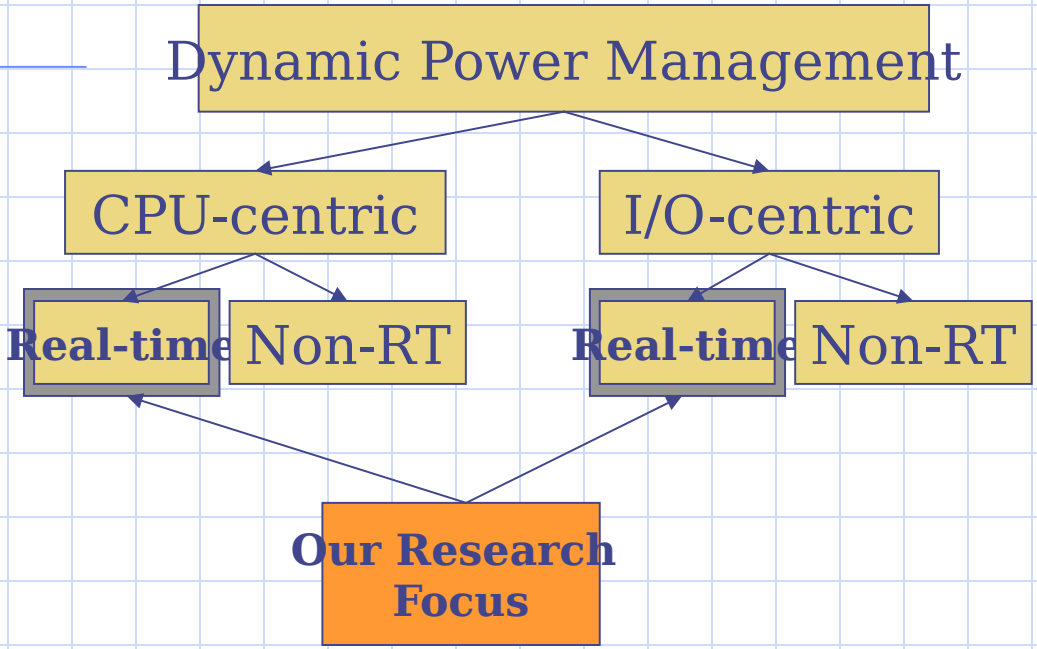
$$H_{q,p} = \sum_{i=0}^{N-1} H_{q,p}(i) \exp\left[- \frac{i^2}{2\sigma^2} \right]$$

- Optimization problem – can be solved by genetic algorithm. Computation is done at the processing center.

RTOS-Driven Power Management

- Real-time system: application tasks have associated deadlines
  - Sensor networks, nuclear power plants, avionics systems
- Power consumption directly influences availability, battery life, and number of field replacements
- Use of Dynamic Power Management (DPM) techniques greatly reduces power consumption

DPM Techniques



Power management through the operating system

Power reduction responsibility is transferred from hardware (BIOS) to software (OS)

OS has global knowledge of CPU workload and devices (APM & ACPI)

CPU-centric DPM

- Previous work
  - Low-Energy EDF scheduler (LEDF)
    - Details presented in April 2001 PI Meeting
    - Dynamically varies CPU voltage/frequency depending on workload (Dynamic Voltage Scaling)
    - Guarantees that all task deadlines are met
  - Implemented on RT-Linux test bed

Prototyping: Hardware Options

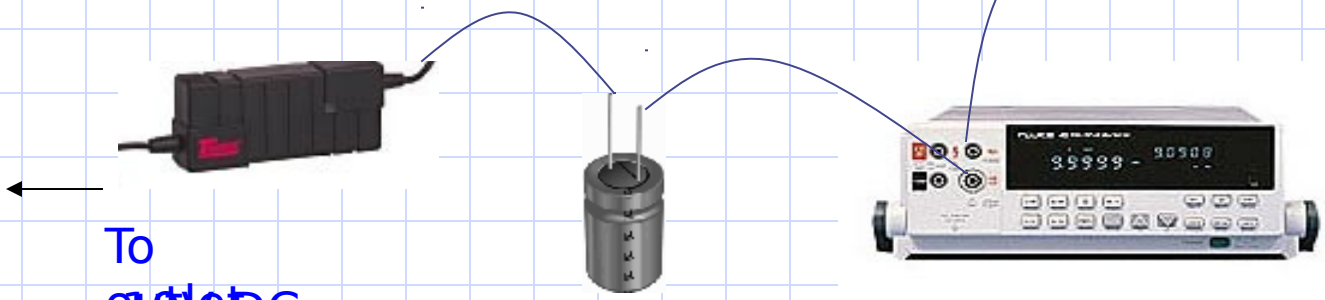
- Hitachi SH4
  - RTLinux port to SH4 still in its primitive stages
  - No speed switching capability
    - Full Power and Halt states
- Intel SpeedStep (High power mode and battery saver mode)
  - Can control the state, but no control over specific frequency/voltage combinations.
  - The hardware controls the voltage/frequency based on average load.
- AMD PowerNow!
  - Can set voltage in 0.05V increments (each voltage has a corresponding MAX frequency).
  - The 1.1 GHz Athlon processor uses a 1.4V core voltage. We can scale the voltage down to 1.25V with a frequency 700MHz.
  - CPU power usage $\propto fV^2$

Experimental Setup

Capacitor used to smooth current

Multimeter used to read current and voltage values

Laptop runs with no battery and display turned off



To outlet

19V DC current

Capacitor

Multimeter

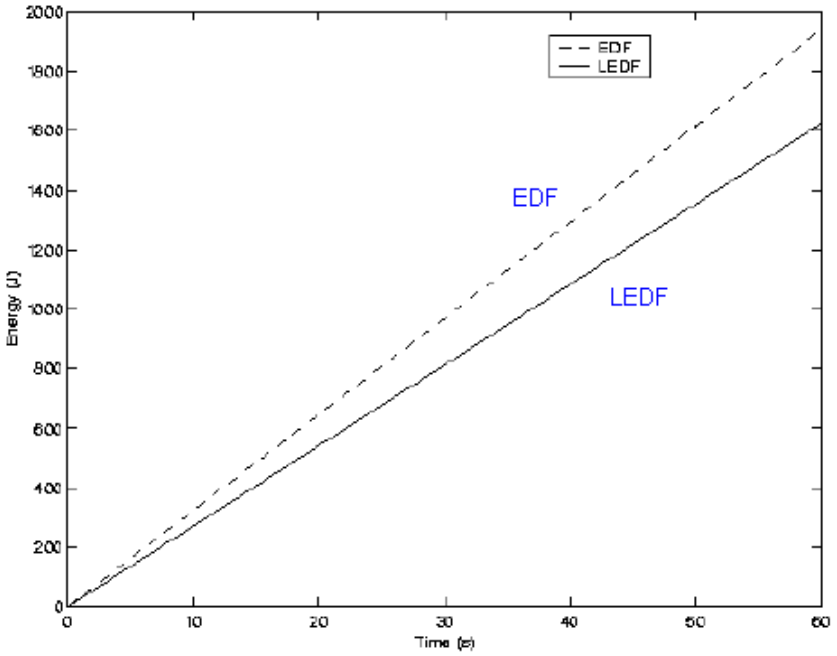
AMD-Athlon Mobile CPU with PowerNow! capability, running RT-Linux v3.0 with LEDF

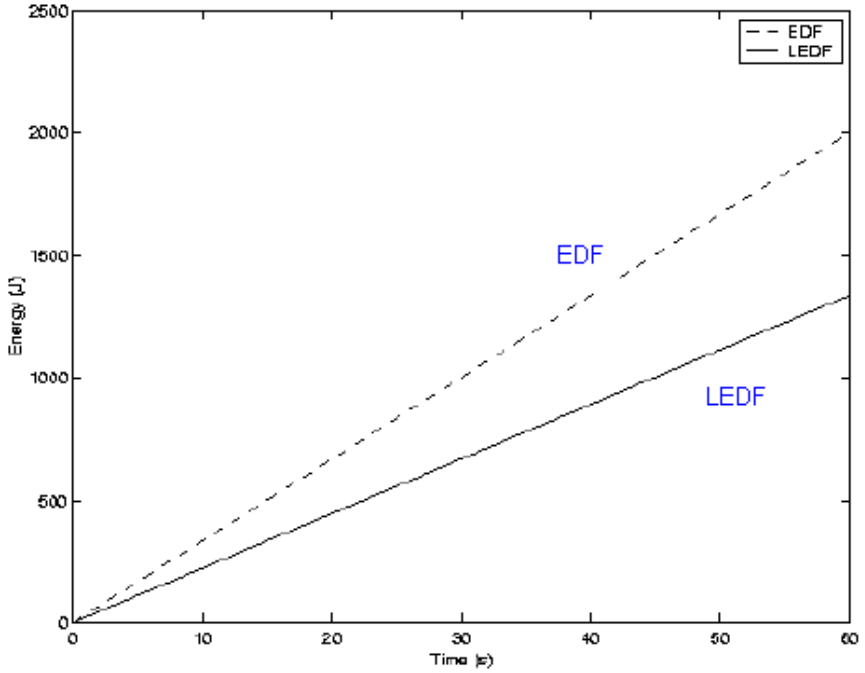
Experimental Results: SensIT Task Sets

Task	# instns (millions)	Exec. time (ms)	Deadline (ms)	Speed (MHz)
Data acq.	2.2	2.0	2.5	1100
Data cache	2.2	2.0	2.65	1100
Classification	3.3	3.0	4.0	1100
Processing	5.5	5.0	6.0	1100
Network Routing	2.25	3.0	7.0	700
GUI update	1.5	2.0	7.0	700
Housekeeping	2.25	3.0	7.0	700

Energy Savings

Data Set	Deadline	Power consumed by EDF	Power consumed by LEDF	Energy savings
Data set 1	Tight	33.85 W	29.38 W	13.2%
Data set 2	Moderate	32.33 W	27.08 W	16.3%
Data set 3	Loose	32.41 W	22.31 W	31.16%





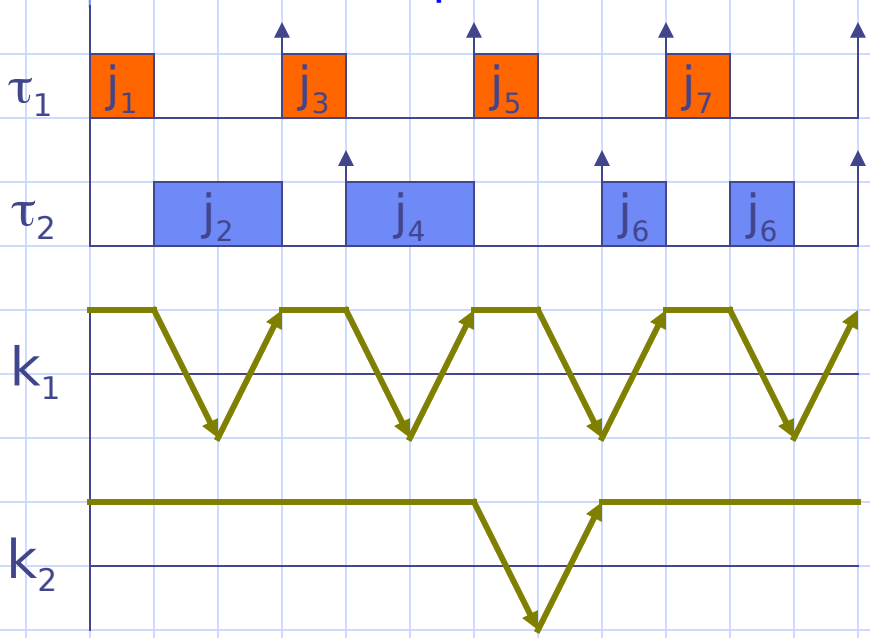
I/O-centric DPM – EDS
(new work since fall 2001)

- EDS (Energy-optimal Device Scheduler) generates energy-optimal device schedules
  - Novel pruning based approach
  - Energy-optimal solutions generated by re-ordering tasks and allowing flexible start times for the tasks
  - Pruning becomes more effective as problem size increases

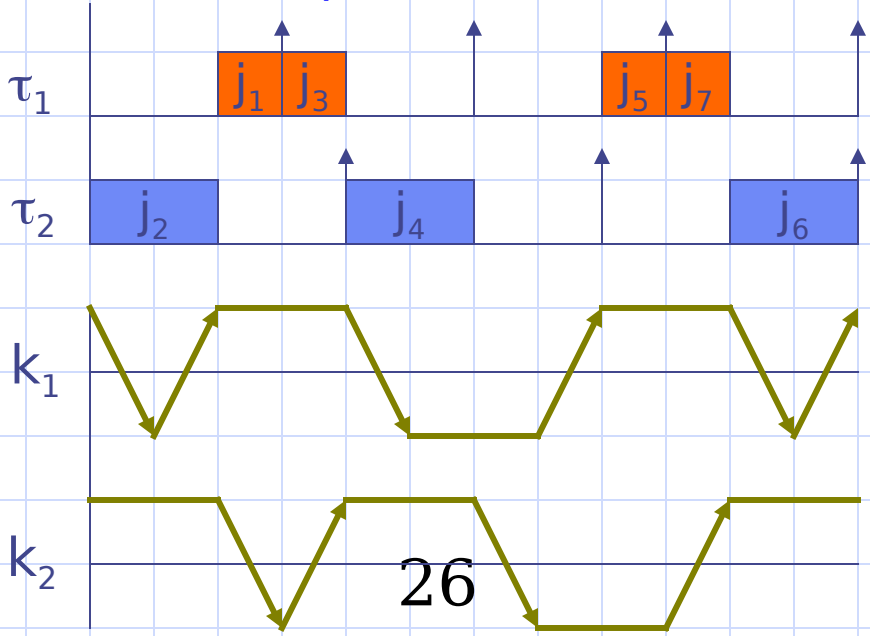
Example

Job	j_1	j_2	j_3	j_4	j_5	j_6	j_7
a_i	0	0	3	4	6	8	9
c_i	1	2	1	2	1	2	1
d_i	3	4	6	8	9	12	12

Before reordering
(non-optimal)



After reordering
(optimal)



Experimental Results

Job set	Total # of vertices			Total # of schedules		
	E.E	EDS	Savings	E.E	EDS	Savings
H=20,J=9	1512	238	84%	312	17	94.5%
H=30,J=11	252931	4110	98%	121016	836	99.3%
H=35,J=12	$2.9x10^6$	13818	99.5%	$1.6x10^6$	3024	99.8%
H=40,J=13	$23x10^6$	43783	99.8%	$14x10^6$	8123	99.9%
H=45,J=14	DNF	84107	-	DNF	17187	-
H=55,J=16	DNF	592091	-	DNF	112363	-
H=60,J=17	DNF	959872	-	DNF	208741	-

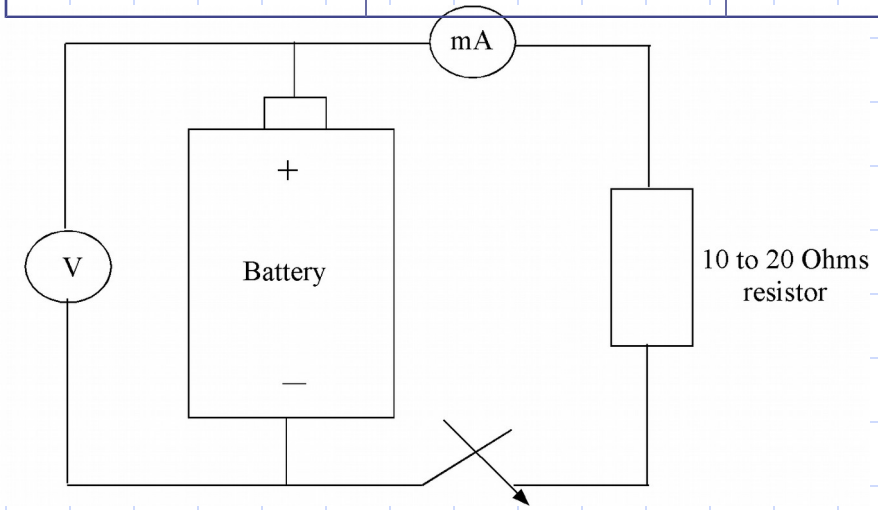
High-level Battery Modeling

(new direction since fall 2001)

- Develop high-level battery models for discharge and recovery
  - Validate battery models on experimental test bed
- Alternating discharge and recovery prolongs battery life
- System lifetime is controlled by rate of switching
  - Rate of switching is determined by discharge and recovery profiles of the batteries
- Discharge profile
  - Empirical analytical model: $V(t)=V_0-V_d(1-e^{-\alpha t}),\ t < LT$
- Recovery profile
  - Empirical analytical model: $V(t)=V_0+V_r(1-e^{-\beta t})$

Experimental Setup

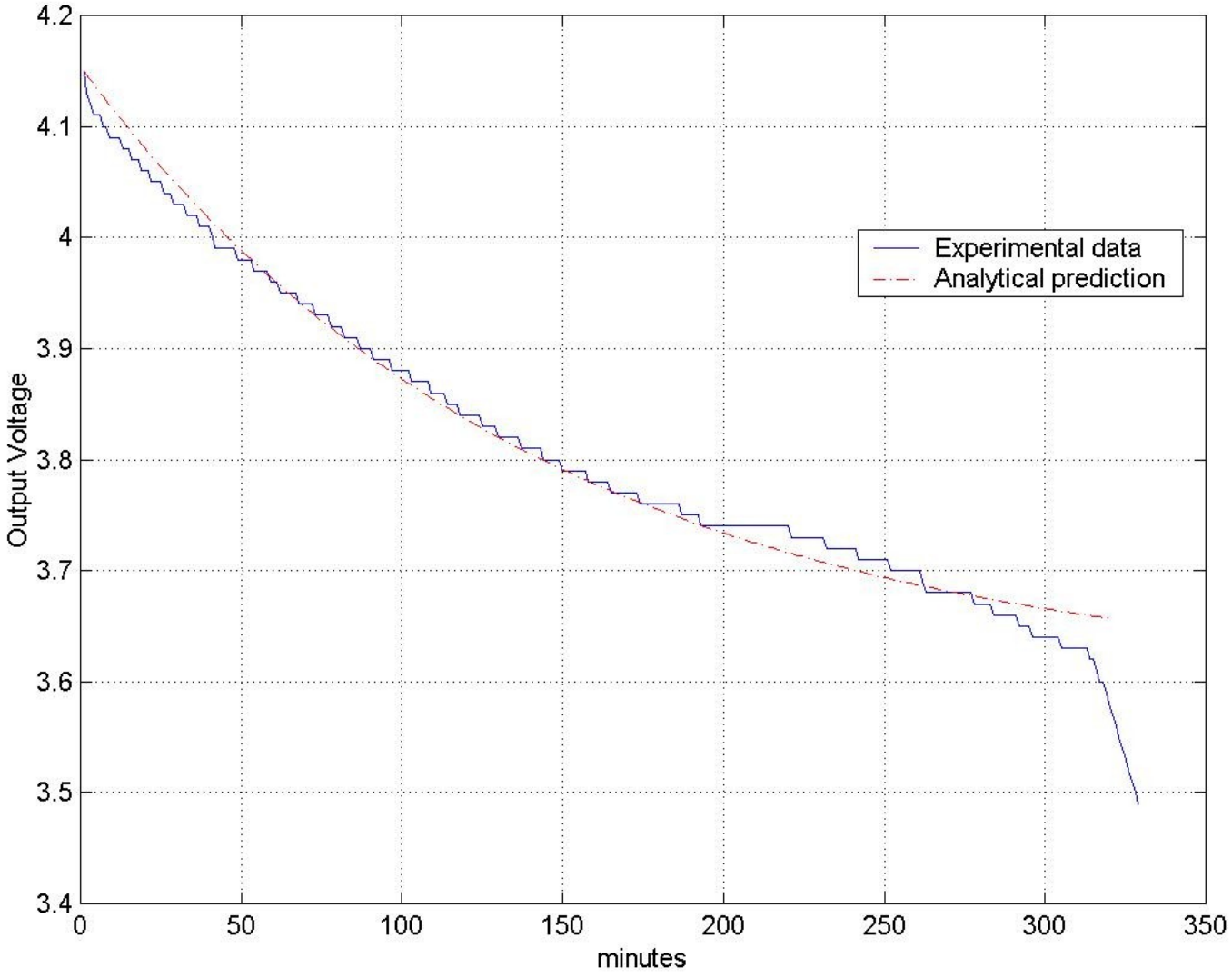
Battery model	Type	Capacity (mAh)	Threshold voltage
SCH8500 (Samsung 8500)	Li-ion	1100	3.6
H690H4 (Nokia 6100)	Ni-MH	900	3.6
Lamina R6P	Alkaline	Data unavailable	1.2



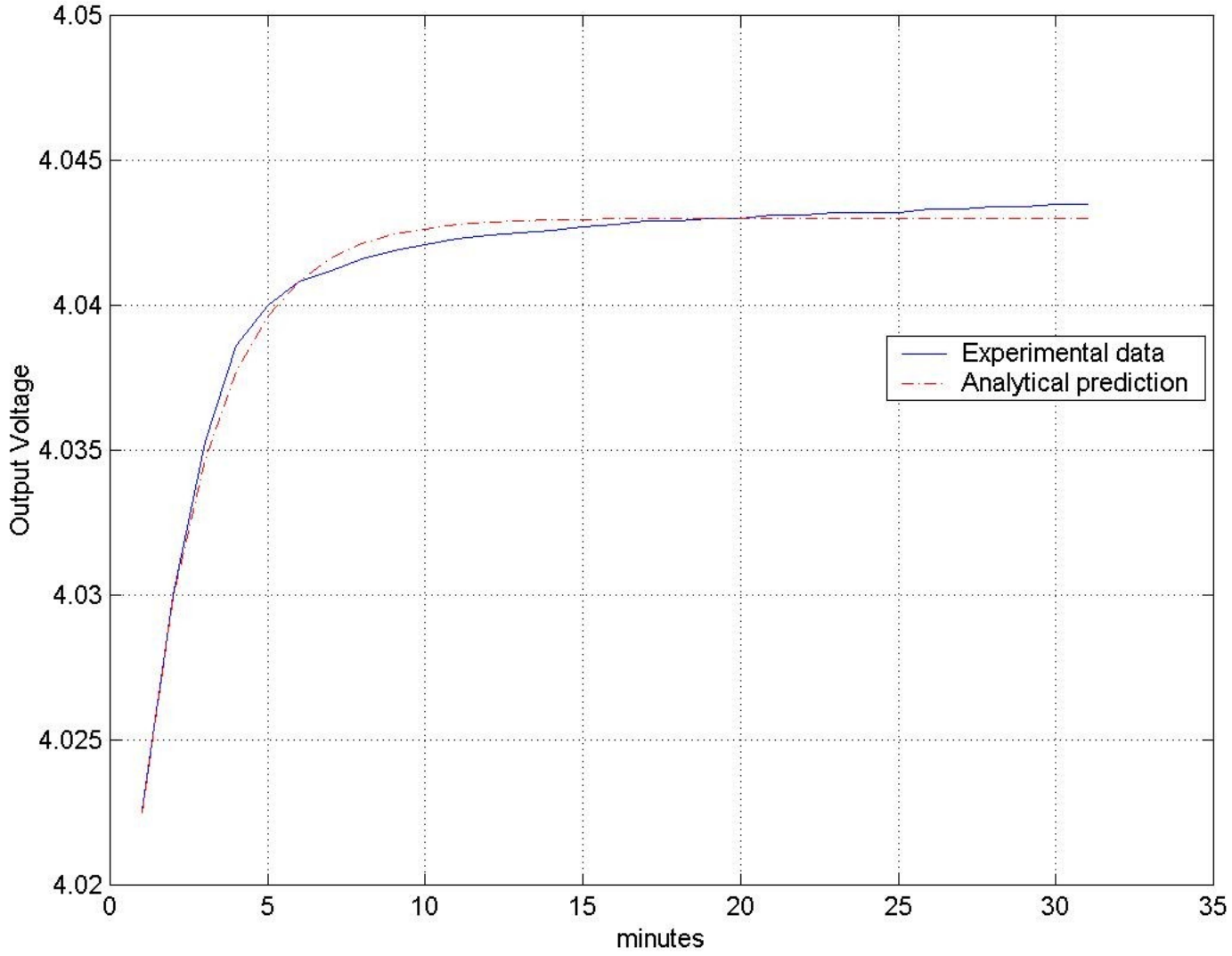
Experiment parameters

- Battery type: SCH8500
- Resistance: 18.5ohms
- Voltage output range: 3.60V to 4.15V
- Current output range: 195mA to 225mA

Discharge Profile



Recovery Profile



Plans for 2002-2003

- Integrate with PSU's mobile code, test target localization, tracking
- For fixed sensor nodes, implement dynamic ad-hoc itinerary planning
- For mobile sensor nodes, dynamic itinerary planning on simulated wireless sensor networks. Performance evaluation between client/server integration paradigm and mobile-agent integration paradigm on the simulated network.
- Energy-driven RTOS design
  - Implement and integrate energy-optimal I/O device scheduling
  - Handle preemption and sporadic tasks, investigate eCOS as an implementation vehicle
  - Adaptive re-prioritization based on available energy
- OS-driven battery scheduling
  - Theoretical modeling, battery scheduling algorithms based on workload
  - Effect of battery resistance on discharge & recovery
- Optimization framework based on coding theory for robust sensor deployment